COMPARING BIAS CORRECTION METHODS TO IMPROVE MODELLED PRECIPITATION EXTREMES

PERBANDINGAN METODE BIAS KOREKSI UNTUK PEMODELAN CURAH HUJAN EKTSRIM

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ABSTRACT

This study aims to analyze and improve modelled extreme precipitation. It was conducted in the German Federal State of Saxony using the WEREX V data set. WEREX V is a model that statistically downscales Global Circulation Model (GCM) data. Inputs for the WEREX V model included GCMs ECHAM 5, HadCM3C and HadGEM2 (sometimes downscaled with Regional Climate Models RCMs REMO, RACMO and CCLM), SRES scenarios A1B and E1, and different model runs. The output of analysis was shown by a boxplot since the WEREX V data set has 120 future projections of precipitation. The model results were verified against observed data obtained from representative meteorological stations, and systematical deviations or biases were identified. To improve the model results, two bias correction methods were applied with special emphasis given to the reproduction of precipitation extremes. Empirical quantile mapping and gamma quantile mapping methods were applied. The ability of the WEREX V ensemble to capture extreme precipitation values varied; this was described in terms of biases. All of the identified correction methods were capable of reducing the bias related to the intensity of extreme precipitation occurrence during the calibration period. The performance of empirical quantile mapping is better than gamma quantile mapping to reduce biases (median value) and uncertainty (inter quartile range value)

Key words: Bias correction methods, extreme precipitation, statistical downscaling, WEREX V data set.

ABSTRAK

Penelitian ini bertujuan untuk mengoreksi bias curah hujan ekstrim keluaran model. Wilayah kajian dalam penelitian ini adalah negara bagian Saxony, German sedangkan data model yang digunakan adalah data WEREX V. Dataset WEREX V adalah data GCM yang yang didownscale secara statistic. Adapun GMC yang digunakan adalah ECHAM 5, HadCM3, HadGem2 dan beberapa RCM (REMO, RAMCO, dan CCLM) dengan menggunakan skenarios SRES A1B and E1. Karena dataset WEREX V terdiri dari 120 data model, maka boxplot digunakan untuk menggambarkan hasil analisis baik untuk identifikasi maupun koreksi bias. Hasil keluaran model dibandingkan dengan data pengamatan (observasi) dari stasiun meteorologi. Dari hasil perbandingan ini, bias akan dideteksi. Untuk meningkatkan akurasi model, bias dikoreksi menggunakan dua metode yaitu Emperical quantile mappinh (EQM) dan Gamma quatile mapping (gamma). Kemampuan model (data WEREX V) untuk menggambarkan curah hujan ekstrim berbeda antar stasiun hal ini digambarkan dengan nilai bias yang berbeda. Metode EQM dan Gamma mampu mengurangi bias maupun ketidakpastian model (uncertainty). Performa EQM lebih baik dibandingkan Gamma. Secara umum EQM mampu mengurangi bias maupun ketidakpastian model

***Kata kunci**: metode bias koreksi, curah hujan ekstrim, statistical downscaling, data set WEREX V*

1. Introduction

Extreme precipitation events have significant socioeconomic impacts on society. Since extreme precipitation events are the main triggers for flash flood and urban floods. Therefore, the assessment of the probability of occurrence and the spatial-temporal patterns of extreme precipitation is essential for human life. Future changes in intensity and frequency of extreme precipitation events requires new adaptation and risk management strategies. Climate models that can quantitatively simulate a range of different, future climate change scenarios have been recognized as instrumental tools that can provide information to facilitate the development of viable adaptation strategies.

Global Circulation Models (GCMs) are comprehensive climate models that are based on physical laws and defined by mathematical equations that are solved using a three dimensional grid over the globe. These numerically coupled models simulate the atmosphere, oceans, land surface and sea ice and offer considerable potential for the study of climate change and its variability. However, they remain relatively coarse in resolution and are currently unable to resolve significant sub-grid scale features. For many impact studies, a finer resolution than that which is provided by GCMs is required. The most important issue with GCMs is the disparity between the spatial resolutions of the modelled results and that which is required of the input data for climate change impact assessment [1] [2] [3].

Downscaling is a method that is used to generate locally relevant, high-resolution data from relatively coarse-resolution, global-scale data (e.g. from GCM or reanalysis results). It bridges the gap between the coarse resolution of climate model results and local scale elements, which is required for various climate change impact assessment models, including the application of climate change scenarios to hydrological models. Downscaling methods have been developed for this purpose [4]. Many downscaling methods have also been described and tested. The choice of downscaling method for a particular study is normally governed by the study objectives, in particular, for which applications the downscaled data will be used for [3][5].

Even though climate models are considered to be the most suitable tools to provide information on future climate projections, these models have inherent systematic errors or biases. Bias is simply defined as the difference between climate model outputs and observed data. Imperfect conceptualization and parameterization, insufficient length of data records, quality of reference data sets and insufficient spatial resolution are identified as the main sources of bias in climate modelling [6].

To reduce these biases, the application of bias correction approaches is required. The main purpose of applying bias correction is to maintain quality of model results. Consequently, the potential for climate impact studies to be based on uncorrected data is eliminated and prevents errors from being transferred from climate models to climate impact models.

Methods to correct bias are necessary to provide proper and suitable climate scenario data for any climate change impact assessment. On the other hand, post-processing of GCM outputs is a prerequisite step to improve the quality of GCM simulations [7][8][9]. Several studies reported that bias correction can improve hydrological model results [10][11][12].

Several bias correction methods have been proposed in the recent past. The development, application, performance, limitation, advantages and disadvantages of bias correction methods are investigated in a number of research projects today. [13] applied seven statistical approaches in a study of error correction methods and empirical statistical downscaling. Methods proposed in this study are local intensity scaling (LOCI), quantile mapping (QM), multiple linear regressions (MLR), multiplelinear regressions with randomization (MLRR), the analog method and the nearest neighbor analog method. Other widely used approaches include the delta change method [14], fitted histogram equalization [15] and gamma-gamma transformation [16]. In recent years, two dimensional bias correction methods have been proposed [17]. These are derived from simultaneous time-averaged corrections of precipitation and temperature. The main reason to apply this method is that most of climate change impact models that simulate hydrology, crop yields or pest and diseases, need temperature and precipitation (T&P) data as forcing fields as a minimum requirement. [18] proposed a new and improved method to correct bias based on a comparative precipitation characteristic.

Based on the aforementioned reasons, this study aims to identify the performance of two bias correction methods to minimize the bias of extreme precipitation.

2. Methods

Study Area. The German Federal State of Saxony was defined as the study area for this study. Saxony is situated in the eastern part of Germany and is one of the sixteen autonomous states of the Federal Republic of Germany.

Data. Observed and modelled data are compared in this study between 1961 and 2000. The modelled data comprises of WEREX V simulations between 1961 and 2100. WEREX V is a model that statistically downscales GCM data. Inputs for the WEREX V model included GCMs ECHAM 5, HadCM3C and HadGEM2 (sometimes downscaled with RCMs REMO, RACMO and CCLM), SRES scenarios A1B and E1, and different model runs.(i.e. a total of 12 input datasets). WEREX V produces 10 equally probable realizations for each input dataset. In total, 120 regional climate simulations were produced. **Table 1** presents the list of GCMs, RCMs, scenarios and model runs with the aforementioned WEREX V datasets.

With regards to the observation data, daily precipitation records of 2 meteorological stations from the German Weather Service (DWD) were obtained as inputs for the analysis. Information about selected stations are shown in **table 2.**

Bias correction was performed with daily data from modelled and observation data. Data between 1961 and 1980 was defined as the calibration data. Bias correction methods were applied based on the season when the record of daily precipitation occurred. Extreme precipitation was analyzed annually and seasonally.

Table 1. List input datasets used in the WEREXV

No	GCMs	RCM	RUN	Scenarios	Symbol
1	ECHAM5	-	L1	A1B	EH5_L1_A1B
2	ECHAM5	-	L1	E1	EH5_L1_E1
3	ECHAM5	-	L2	A1B	EH5_L2_A1B
4	ECHAM5	-	L3	A1B	EH5_L3_A1B
5	ECHAM5	CLM	L1	A1B	EH5_CLM_L1_A1B
6	ECHAM5	CLM	L2	E1	EH5_CLM_L2_A1B
7	ECHAM5	RACMO	L3	A1B	EH5_RACMO_L3_A1B
8	ECHAM5	REMO	L3	A1B	EH5_REMO_L3_A1B
9	HC3C	-	L1	A1B	HC3C_L1_A1B
10	HC3C	-	L1	E1	HC3C_L1_E1
11	HCG2	-	L1	A1B	HCG2_L1_A1B
12	HCG2	-	L1	E1	HCG2_L1_E1

Tabel 2. List of meteorological stations

No	Station Name	Altitude (meter)	Lat	Long
1	Dresden-Klotzsche	227	51.13	13.75
2	Fichtelberg	1213	50.43	12.95

A schematic overview of the methodology that was applied in this study is described as follows:

a) Data collection and quality check for both modelled and observed data.
b) Extreme precipitation analysis: The threshold method was applied using threshold values defined at 99th percentiles.
c) Modelled results were compared with observed data, using the empirical Cumulative density function (ECDF) and associated biases were identified.
d) Two bias correction methods were tested and evaluated per station for a calibration period (1961-1980) to correct the bias. Emphasis was placed on precipitation extremes.

Daily precipitation was the variable that was subjected to bias correction. In general, the objectives of bias correction are to correct the mean, variance and/or the whole distribution of the variable of interest.

Extremes value analysis. Extreme precipitation was analyzed with observation and modelled data. The Peak Over Threshold (POT) method was selected with thresholds defined at 99th percentiles. For temporal analysis, extreme precipitation thresholds were analyzed annually, seasonally and on a daily basis. The precipitation analysis was only applied to wet days. A wet day was defined as a 24-h period when the amount of precipitation was equal to or greater than 1 mm.

Empirical quantile mapping (EQM). Quantile mapping or also known as quantile matching is widely applied to correct biases and generally performed better than other bias correction methods [13][17][18][19][20][21][22]. The quantile mapping method is derived by calculating the empirical probability density function (PDF), and uses the cumulative distribution function (CDF) to correct the raw data. To correct the bias with this method, the Qmap package in R software (https://www.r-project.org/) was used. This method consists of two steps. First, fitQmapQUANT was called to estimate the value of the empirical cumulative distribution function of observed and modelled data. Then, doQmapQUANT was called to perform quantile mapping based on the estimated value.

Gamma Quantile Mapping (Gamma). There are several theoretical distributions that can be used to describe the probability distribution function of precipitation. The gamma distribution is commonly used because it has the ability to represent typically asymmetrical and positively skewed distributions of daily precipitation. Gamma quantile mapping assumes that the probability distributions of both observed and modelled daily precipitation data sets can be approximated using a *Gamma* distribution[8].

Quantile mapping using gamma distribution was performed using the Qmap package in R. Like empirical quantile mapping, distribution quantile mapping is also comprised of two steps to correct the bias. First, fitQmapDIST was called to determine the distribution of observed and modelled data. The associated parameters and transfer functions derived from the distribution were returned. Then, doQmapDIST was called to convert the distribution of the modelled data to match the distribution of the observed data using the identified transfer function.

The Bernoulli Gamma (Bern gamma) distribution was chosen, whereby the Bernoulli distribution is used to model the occurrence of zero and non-zero values. Correction is performed with the Gamma distribution having shape and scale parameters [19].

3. Result and Discussion

Extreme Precipitation. Extreme precipitation analysis for 99th percentile threshold for the stations Dresden and Fichtelberg are shown by season (i.e. winter (DJF), spring (MAM), summer (JJA), autumn (SON)) and per year (Fig.1).

Annual analysis of extreme precipitation threshold values showed that the highest threshold value occurred in Fichtelberg which is located in a mountainous region. Based on these observations of annual threshold values, it can be seen that annual extreme threshold values are strongly dependent on the orographic structure of study area. The highest threshold extreme value occurred during summer (JJA) for both stations and the lowest extreme value occurred during winter (DJF).

The highest extreme threshold value for the 99th percentile is 45mm. The lowest extreme threshold value is 25 mm for the 99th percentile.

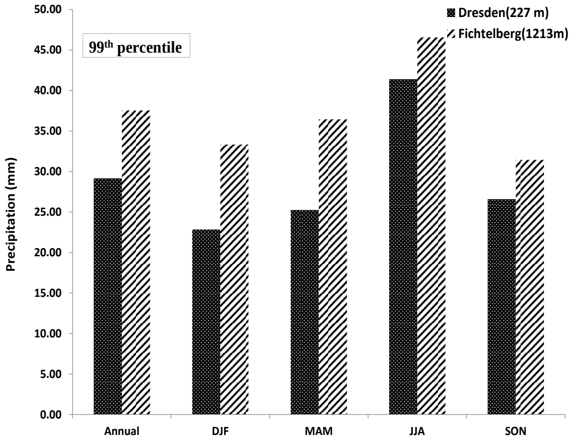

Figure 1. **The intensity of precipitation extreme threshold values (99th percentiles) based on observed data collected for two stations.**

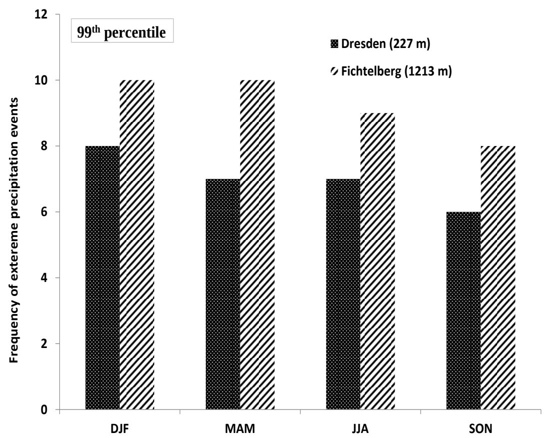

Figure 2. **The frequency of precipitation extremes exceeding the 99th percentile threshold for two stations.**

The frequencies of precipitation extremes for two stations are shown in Figure 2. Amounts of precipitation that are above the threshold value are considered as extreme precipitation events. The most frequent extreme precipitation event occurred at Fichtelberg. As the intensity of extreme precipitation changes, the frequency of extreme precipitation also varies depending on altitude. Furthermore, the temporal distribution shows that the highest number of extreme precipitation events occurred in winter (DJF) and spring (MAM).

Modelled Data (Bias Detection). There were substantial differences in the ability of models to reproduce precipitation values. The extreme values detected by models in this study are shown as bias from observed values. Since the WEREX V data set has 120 future projections of precipitation, a box plot was used to show all of the projection biases. Figure 3 and 4 show how many millimetres of modelled precipitation values deviate from the observations for the stations Dresden and Fichtelberg, respectively.

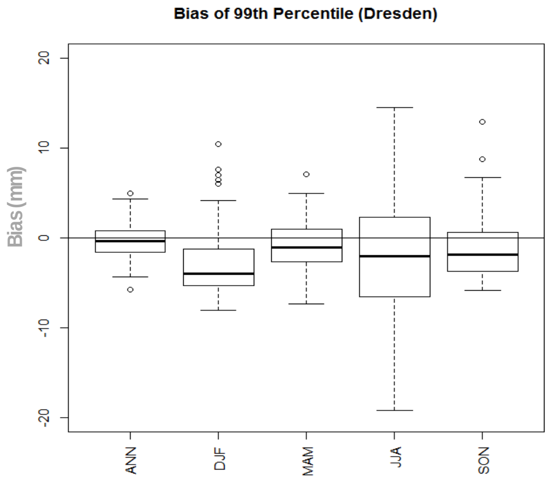

Figure 3. **The biases of modelled intensity data based on 120 projections using the WEREX V dataset for Dresden.**

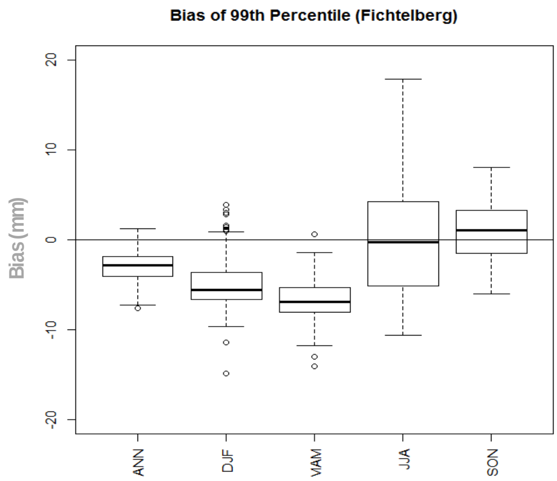

Figure 4. **The biases of modelled intensity data based on 120 projections using the WEREX V dataset for Fichtelberg.**

Most of the modelled results for Dresden had a negative median of biases. This means that most of the models underestimated extreme precipitation values. It can be seen that the largest biases occurred in the summer (JJA) and the smallest biases occurred in the winter (DJF).

The bias variability of model is shown using the interquartile range (IQR) statistic, which quantifies how spread out data points in a set are. The larger the IQR, the more spread out the data, while the smaller the IQR, the more spatially close the data points cluster around the mean. The highest IQR is found for Dresden station corresponds to data collected during the summer (JJA) and the lowest variability occurred during the spring (MAM).

The annual bias for data in the 99th percentile ranged from -5 mm to 5 mm. Summer biases for 99th percentile has range about -20 mm to 15 mm. While winter biases for data in the 99th percentile ranged from -7 mm to 5 mm.

Figure 4 shows the biases of modelled data for Fichtelberg station. The pattern of threshold for precipitation extremes was the same pattern as the one observed with the data from Dresden station. All the median biases had negative values. This implies that most modelled extreme values for this station are too low. It also corresponded to the season when the events occurred, In Summer and autumn some models overestimated and other underestimated extreme values

The large bias associated with the summer months is related to the convective process. The particular process is very difficult to estímate with currently available climate models [23][24]. Consequently, the related uncertainties contribute to the large biases observed and are considered to be most difficult to correct.

Bias Correction. Empirical quantile mapping and Gamma quantile mapping methods were applied to the precipitation values from WEREX V dataset. Bias correction methods were performed with projected and observed data records spanning 20 years (i.e. from 1961 to 1980). The observed data was defined as the reference precipitation data for bias correction for the stations of interest.

Figures 5 to 6 represent uncorrected and corrected intensity threshold values of precipitation extremes found with each method and for each season. The annual bias correction for Dresden (Figure 5) showed that all of the correction methods that were applied to correct the modelled data could reduce the biases for Dresden and Fichtelberg. Moreover these bias correction methods also can reduce the associated uncertainty in the modelled data. The boxplot reveal that these methods reduced both the median and the inter quartile range (IQR) of the biases

Figure 6 showed biases before and after correction for all seasons in Dresden and Fichtelberg. The bias correction for these seasons revealed that all bias correction methods were able to consistently correct the biases, while performances varied for biases within methods. Empirical and gamma quantile mapping methods can reduce the median biases and uncertainty (IQR) for Dresden and Fichtelberg.

The empirical quantile mapping method was identified to perform best in all season and all stations. This method was able to correct the medians biases nearly perfectly (i.e. approaching zero) except for Fichtelberg in winter season. Eventhough empirical quantile mapping was able to correct the medians biases nearly perfectly, but in some cases for instance in Dresden during DJF and SON produced larger range of max – min value of bias than gamma method. It shows that this method was not able to correct bias for outlier (very extreme value). The bias correction method with distribution approach such as gamma quantile mapping shows best performance.

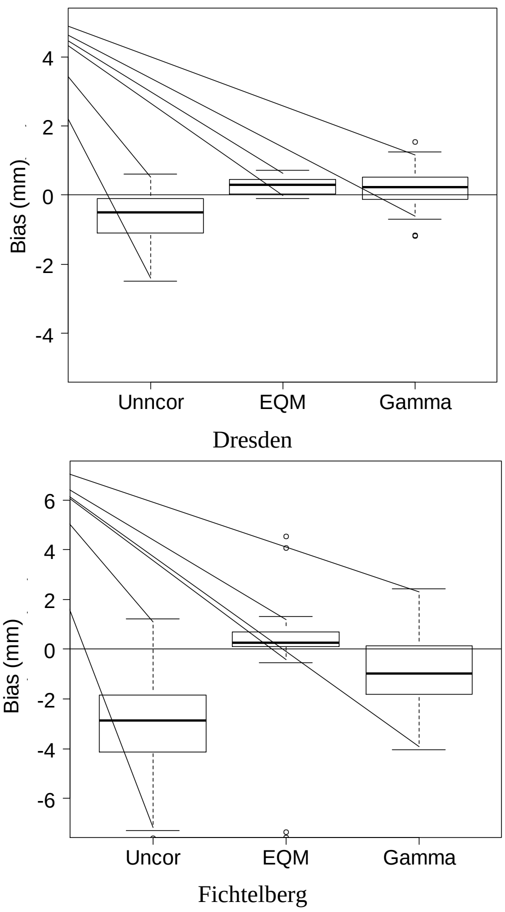

Figure 5. Uncorrected and corrected biases associated with the annual analysis of precipitation data for Dresden and Fichtelberg.

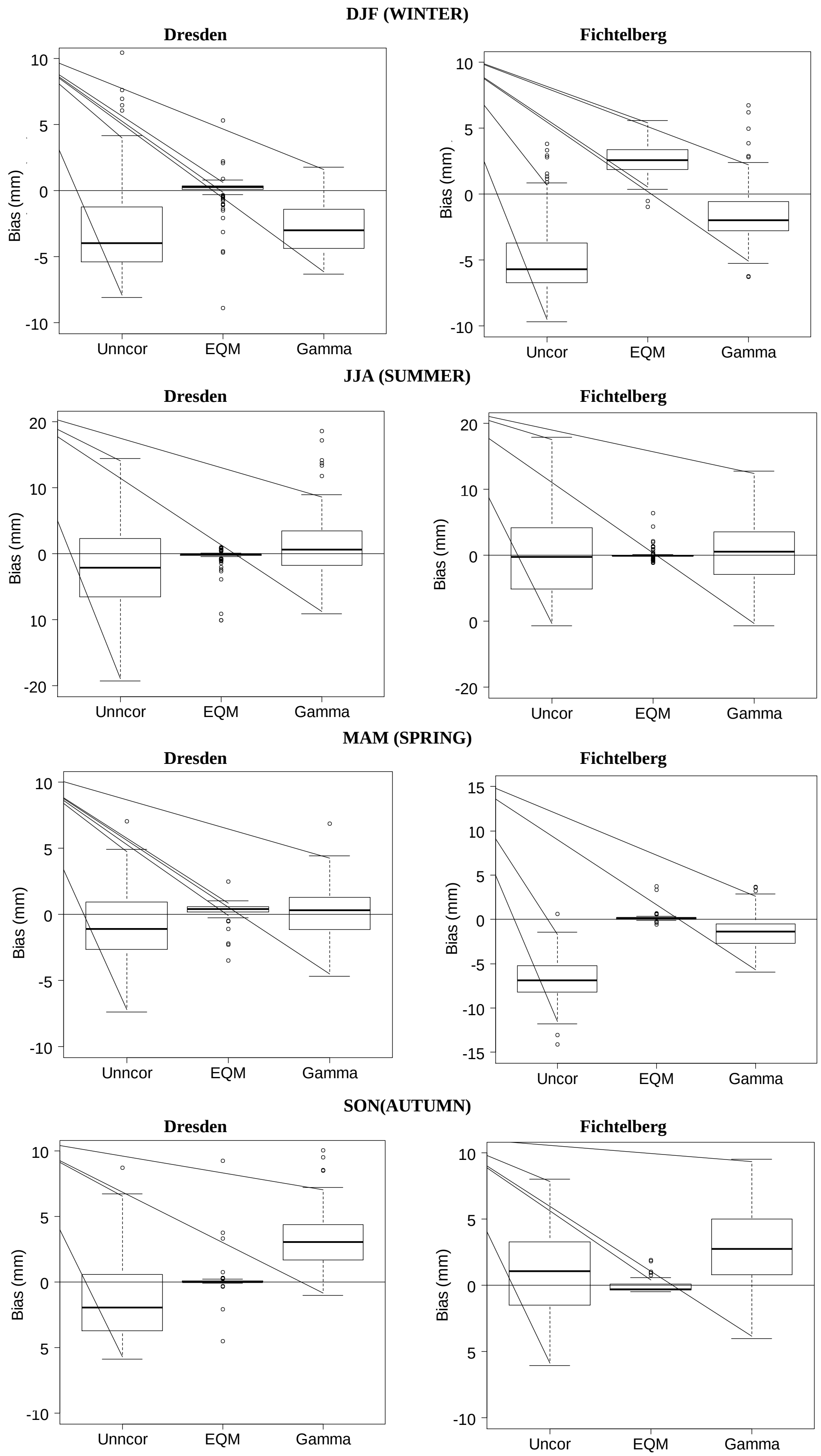

Figure 6. A comparison of uncorrected and corrected biases associated with the summer, spring, autumn and winter analyses of precipitation data for Dresden and Fichtelberg.

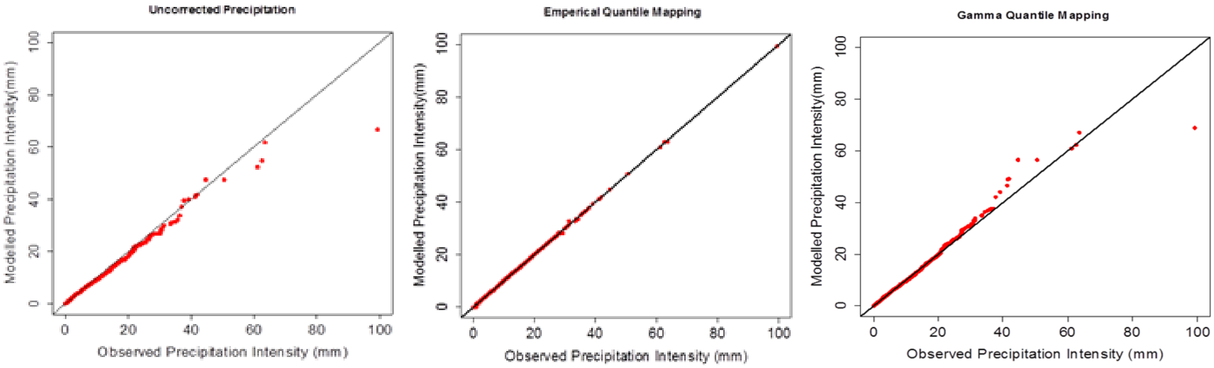

Figure 7. Annual quantile-quantile plot of 00_EH5_L1_A1B projection, for calibration periods (1960-1980) in Dresden.

The quantile-quantile plot was used to assess the performance of bias correction methods for each projection. Figure 7 shows the quantile-quantile plot observation against the corrected and uncorrected 00_EH5_LI_A1B projection for Dresden station during calibration. Results with empirical quantile mapping could match the extreme values perfectly, even with respect to maximum values. Correction with gamma quantile mapping shows no significate improvement of the distribution, extreme values are not corrected properly.

4. Conclusion

Precipitation extreme values vary depending on altitude, and season. Based on the analyses conducted for the selected stations, the highest extreme threshold value was found in Fichtelberg (mountainous area). Based on seasonal analyses, the highest threshold extreme value was found during the summer.

Modelled precipitation extremes of the WEREX V data set were mostly undersetimated in comparison to obersvations. These values were affected by variable biases for each station, and each season. The highest bias was found during the summer.

This study shows that emperical and gamma quantile mapping methods are capable of reducing biases and improving the modelled data to some extent, during calibration periods. The bias correction method not only corrected modelled precipitation values, but also had different influences on the resulting threshold of extreme precipitation. However, the quality of corrected modelled precipitation data is strongly depended on which method is selected. The performance of the bias correction approaches varied across different stations and seasons. Empirical quantile mapping was found to be the best bias correction method. The method was able to correct most of projected precipitation extreme and frequency of extreme precipitation event values. Moreover, this method had a narrow range of variability

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